

A Clustering Approach to Wind Power Prediction based on Support Vector Regression

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Abstract

A sustainable production of electricity is essential for low carbon green growth in South Korea. The generation of wind power as renewable energy has been rapidly growing around the world. Undoubtedly wind energy is unlimited in potential. However, due to its own intermittency and volatility, there are difficulties in the effective harvesting of wind energy and the integration of wind power into the current electric power grid. To cope with this, many works have been done for wind speed and power forecasting. It is reported that, compared with physical persistent models, statistical techniques and computational methods are more useful for short-term forecasting of wind power. Among them, support vector regression (SVR) has much attention in the literature. This paper proposes an SVR based wind speed forecasting. To improve the forecasting accuracy, a fuzzy clustering is adopted in the process of SVR modeling. An illustrative example is also given by using real-world wind farm dataset. According to the experimental results, it is shown that the proposed method provides better forecasts of wind power.

Key Words : Support vector regression, Wind power, Fuzzy clustering, Short term prediction

I. Introduction

Wind is a clean and cheap source of energy but, due to its intermittency and volatility, the availability as a form of the power is unknown in advance[1]. As there have been many advances in wind turbine technology and wind resource identification skill, its estimated electrical power includes more considerable fluctuations. This uncertainty makes it difficult to integrate the wind power into large-scale electricity grid. Such a challenging situation motivates researches to the wind power forecasting issue[2, 3].

Models for the wind power forecasting are broadly classified into physical and statistical ones[3]. Physical models are appropriate for the long-term wind power forecasting. On the other hand, some statistical methods are widely adopted in the short-term forecasting. Among them, the most famous one is Autoregressive integrated moving average (ARIMA) proposed by Box and Jenkins[4]. For example, an ARIMA approach incorporated with wavelet decomposition was proposed[5]. Recently artificial intelligence (AI) techniques including fuzzy logic, neural network, support vector machine and some hybrid methods have been employed for the wind power forecasting[1, 2, 6-8]. It is shown that some AI techniques outperforms statistical approaches in terms of minimizing prediction errors.

In particular, support vector regression (SVR) has been much attention to pattern classification problems. It is reported that, compared with neural network, SVR gives smaller prediction error in the generalization stage. This paper deals with support vector regression for the wind power forecasting. In this paper, a fuzzy clustering approach is employed in order to improve the forecasting accuracy in the SVR modeling. Chapter 2 describes the proposed method for the wind power forecasting. In Chapter 3, numerical illustrations are given by using real-world dataset. Finally, our works are concluded with summary in Chapter 4.

2. The Method Proposed

Support vector machine (SVM) developed by Vapnik[9] is a classification technique based upon an optimum separating hyperplane (OSH) which maximizes the minimum distance between classes. A nonlinear and higher dimensional mapping should be applied when OSH is not found in the original space. This is illustrated in the following figure[10].

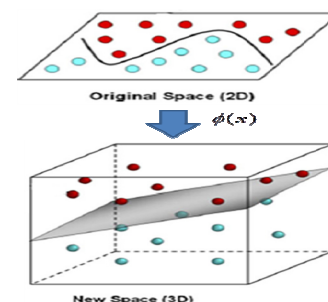


Fig. 1. An OSH in the higher dimensional feature space[10]

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This can be extended for regression problems. The basic idea of support vector regression (SVR) is to map the feature vector x into a higher dimensional space by using a nonlinear mapping $\phi(x)$. The resulting regression line is written as:

$$f(x) = \sum w_i \phi(x_i) + b \quad (1)$$

where w_i and b are regression coefficients. The equation is found by minimizing the following objective function.

$$\Phi(w, \varepsilon) = w^T w + C \cdot \sum L_\varepsilon(y) \quad (2)$$

where C is a regularization constant and $L_\varepsilon(y)$ is an ε -insensitive loss function defined by:

$$L_\varepsilon(y) = \begin{cases} 0, & |f(x) - y| \leq \varepsilon \\ |f(x) - y| - \varepsilon, & \text{elsewhere} \end{cases} \quad (3)$$

Substituting Eq. (3) into Eq. (1) yields:

$$\Phi(w, \varepsilon) = w^T w + C \cdot \sum (\xi + \xi^*) \quad (4)$$

where ξ and ξ^* are slack variables which are illustrated in the following figure.

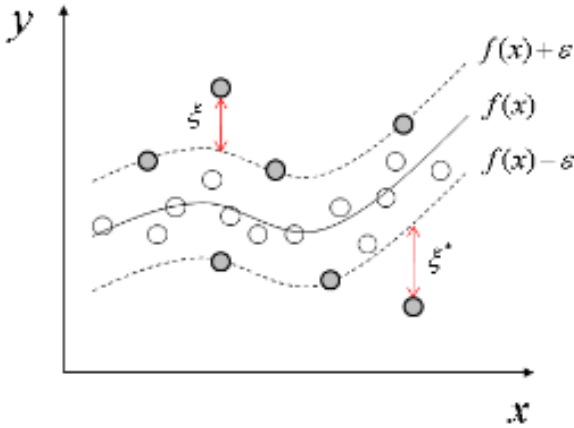


Fig. 2. Support vector regression with ε -band

As explained so far, the optimum regression line depends on two parameters C and ε which should be specified. The parameter setting is significant in forecasting accuracy. This will be illustrated later by example of wind speed dataset. Moreover, choice of kernel has to be considered as well. Kernel function is an inner product of two transformed feature vectors and it is written by $k(x_i, x_j) = \phi(x_i)^T \phi(x_j)$. In the literature, there are several kernel functions, namely linear, polynomial, and Gaussian kernels. Among them, Gaussian kernel is most commonly used and therefore adopted in this work. Gaussian kernel is defined by:

$$k(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / \sigma^2) \quad (5)$$

where $\|\cdot\|$ and σ denote the 2-norm and the kernel bandwidth respectively. It is noted that both modeling accuracy and predicting capability are affected by the value of σ . This will be discussed in the subsequent sections.

An upper limit of wind power generation can be calculated from wind speeds. The following figure illustrates the power curves at different sound levels for the V52-850 turbine manufactured by Vestas[11].

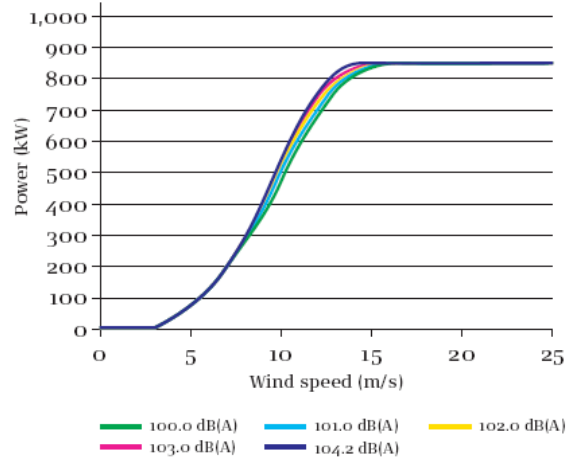


Fig. 3. Typical power curves of turbine[11]

The power curves indicate that wind speed modeling is essential for the wind power prediction. This paper employs SVR for the purpose of wind speed forecasting. Let (y_1, y_2, \dots, y_t) denote wind speed observations given as time series data at time t . The objective is to obtain \hat{y}_{t+k} , a forecast value of k -step ahead wind speed. Our proposed SVR uses recent P observations to produce \hat{y}_{t+k} . Sometimes, heterogeneous input observations may cause a deficiency in the process of modeling and parameter tuning. This subsequently leads to unstable forecasting. In order to cope with this problem, a fuzzy clustering technique is incorporated with SVR in this paper. The figure below outlines the proposed method, where the subroutines are described in the next section.

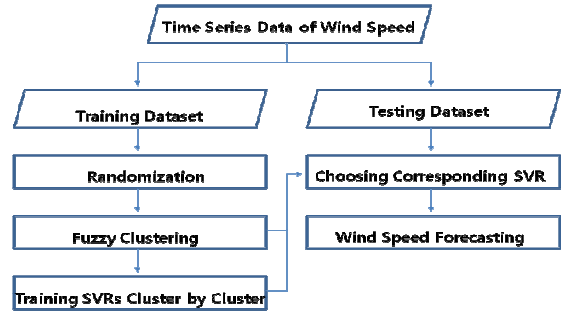


Fig. 4. Procedure of the proposed method for wind speed forecasting

3. Application to Wind Speed Forecasting

The wind speed by meter per second (mps) was measured in Spring 2011 by a wind farm site located at Gunsan, South Korea. About 4400 cases in the dataset are considered for numerical illustrations. The dataset is divided for model training and testing. In particular, a randomization is applied to the training dataset in order to reduce a localization effect. Two hundred cases are included in the training dataset. We set $p=3$ and $k=1$ for illustration.

To begin with, the dataset is dealt with by a single SVR. After some repetitive experiments, the parameter setting is determined as $(C, \nu, \sigma) = (20, 0.15, 0.007)$. Note that ν denotes a lower limit for the fraction of support vectors. This model parameter was employed instead of ϵ for the sake of convenience. The modeling is conducted by using Libsvm, a Matlab toolbox provided in [12]. The figure below shows a calibration-prediction(C-P) plot obtained by Matlab.

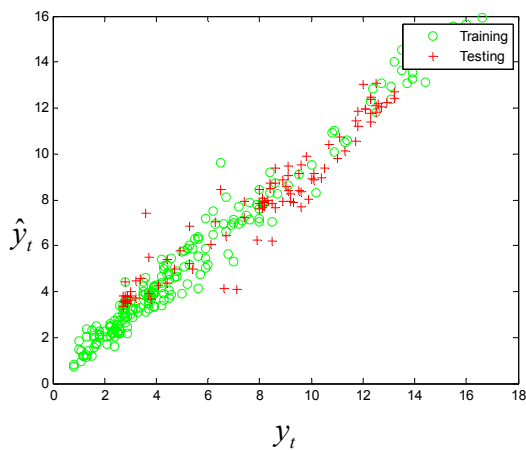


Fig. 5. Calibration-Prediction Plot of Single SVR

Root mean square error (RMSE) is commonly used to evaluate modeling accuracy and forecasting capability. This is defined by:

$$RMSE = \sqrt{\sum_{j=1}^n (y_j - \hat{y}_j)^2 / n} \quad (6)$$

In Fig. 5, RMSEs are 0.6207 and 1.0149 for the training and the testing datasets respectively. The coefficient of determination R^2 is also useful as a measure of modeling accuracy. In this case, the values of R^2 are 97.39% and 91.65% respectively.

Now, a clustered SVR (C-SVR) which we propose in this paper is illustrated. First, a fuzzy clustering is done to the training dataset. Here, two-cluster case is considered for illustration. Similarly, hyper-parameter settings are found by preliminary trials. They are $(C, \nu, \sigma) = (20, 0.2, 0.01)$ for cluster 1 and $(C, \nu, \sigma) = (30, 0.25, 0.001)$ for cluster 2

respectively. The training RMSEs are 0.5579 and 0.8684 for each cluster. Recall that RMSE for single SVR was 0.6207. The C-P plot for C-SVR is given by Fig. 6. In this figure, the values of R^2 are 88.93% for cluster 1 and 93.03% for cluster 2 respectively.

The forecasting results for the testing dataset are displayed in Fig. 7. Note that one hundred cases are considered in the testing dataset. Fig. 7 shows that C-SVR produces better forecasting values. This observation can be confirmed by calculating RMSE and R^2 , which are 0.9101 and 93.19% respectively. Therefore the numerical experiment indicates that, compared with SVR, the proposed C-SVR improves the predicting accuracy in terms of RMSE about 10%.

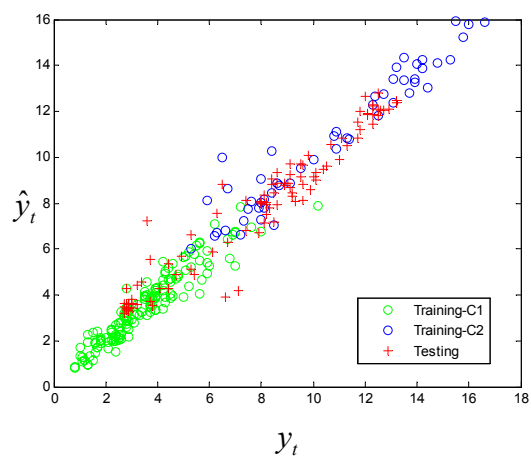


Fig. 6. Calibration-Prediction Plot of Clustered SVR

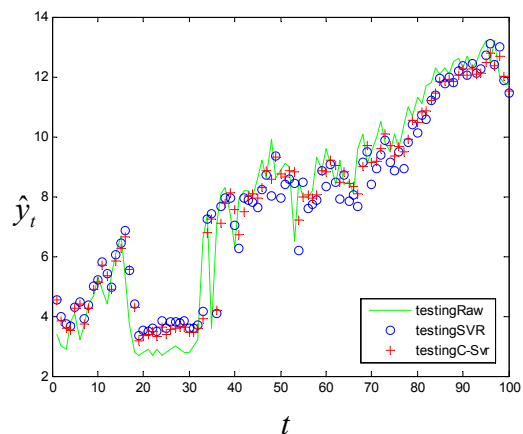


Fig. 7. Forecasting Results for the Testing Dataset

Although C-SVR has a potential to improve RMSE, two cautious points should be addressed. One is that its predictive performance could be sensitive to the choice of training and testing datasets. We can see that the datasets in the above figures have similar ranges each other. Moreover, cluster members are not skewed but spread very well. These are necessary conditions where C-SVR works appropriately. On

the contrary, the testing dataset which depicted in Fig. 8 is highly ‘unbalanced’. In other words, most of sample cases in the testing dataset belong to cluster 1 of which members are far smaller than ones of cluster 2. In such case, whereas C-SVR provides good predictions for cluster 1, its performance is unreliable for cluster 2. Henceforth, the gain of C-SVR will be relatively deteriorated. Forecasting values of C-SVR and SVR are graphically given in Fig. 9. A way to avoid such a risk is to increase sufficiently the size of dataset.

Another point in SVR modeling is concerned with the forecasting step size. Although only single-step ahead forecasting was illustrated here, multi-step ahead forecasting is more popular in real-world applications. Note that a short-term forecasting of wind speed can be in general established in the order of several days and sometimes from minutes to hours[8]. Fig. 10 shows that RMSEs are getting higher according to the step size k . If $k \geq 8$, there is little difference between C-SVR and SVR in terms of RMSE.

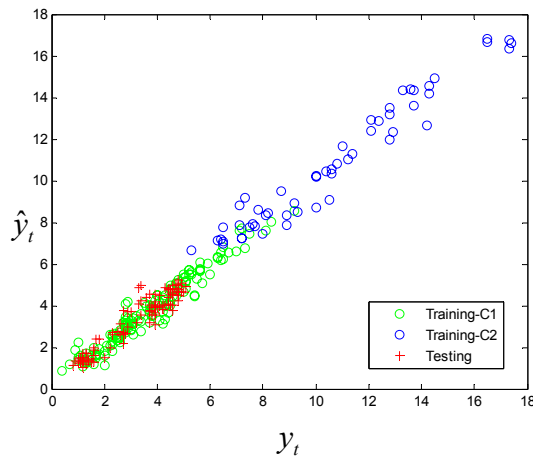


Fig. 8. Calibration-Prediction Plot of C-SVR for Unbalanced Dataset

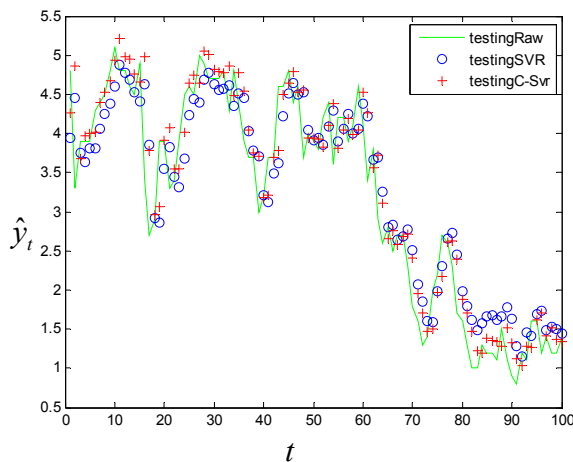


Fig. 9. Forecasting Results for Unbalanced Dataset

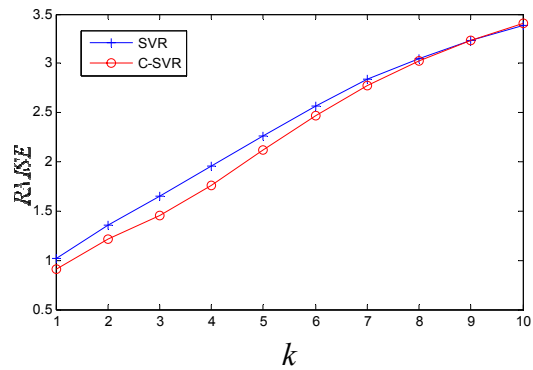


Fig. 10. RMSE and Step Size

One thing to keep in mind is that the hyper-parameter tuning in SVR is essential for better forecasting accuracy. For this purpose, many regularization techniques have been introduced in the literature. Grid search, genetic algorithm, particle swarm optimization, and statistical response surface design are those examples[8, 13, 14]. The parameter settings of this research were found by a simple back-and-forth search. This is why there would be more room for improvement with the proposed C-SVR.

4. Conclusions

SVR is a powerful technique for solving function estimation problems and therefore has a potential for prediction applications. This paper proposes to use SVR for the wind speed forecasting. In particular, by incorporating a fuzzy clustering approach with SVR, we attempt to improve the forecasting accuracy which is measured by RMSE. According to numerical experiments with real-world dataset, our presented method has an advantage of reducing RMSE at least 10%.

As mentioned earlier, the hyper-parameter tuning is essential in SVR. Its forecasting accuracy can also be affected by clustering results. These issues will be investigated by using more experiments. Adopting a wavelet based de-noising as a preprocessing step for wind speed forecasting would be fruitful for future research.

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